Serial Retinex Algorithm for Time-Sequential Processing

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Abstract

The Retinex is a human perception-based image processing algorithm which provides color constancy and dynamic range compression. A real-time implementation of the Retinex is required to meet the needs of various potential users. The Retinex processing contains a relatively large number of complex computations, thus to achieve real-time performance using current technologies requires specialized hardware and software. As one of the solutions by approach from software, in this paper, we propose a serial Retinex algorithm for time-sequential processing. In our algorithm, multi-scale surround images are integrated to a single surround field which is applied to Center/Surround SSR model. With progress of processing time, the appearance will be gradually improved and the processing region will be gradually spread out. By an experiment for still images and a simulation experiment for motion pictures, we verified the effectiveness of the proposed algorithm.

Introduction

Retinex image enhancement algorithm, which was proposed by Land[1]-[5] and McCann[6], is an automatic image enhancement method that enhances a digital image in terms of dynamic range compression, color independence from the spectral distribution of the scene illuminant, and color/lightness rendition. The digital image enhanced by the Retinex image enhancement algorithm is much closer to the scene perceived by the human visual system, under all kinds and levels of lighting variations, than the digital image enhanced by any other method. According to Land, human visual system has the functions that recognize the world without affected by spatially non-uniform distribution of illuminant. Simply, the image *I* captured by camera is equivalent to the product of the reflectance *R* and illuminant distribution *L*. According to $R \cong I/L$, we can restore reflectance *R* from Image *I* by inferring illumination *L*.

To estimate the distribution of illumination *L*, the Retinex algorithm has been improved during past forty years. The papers on appearance improvement of color images based on MSR(Multi-Scale Retinex)[6]-[11], which is integrated by multi numbers of SSR(Single-Scale Retinex), can suppress the bandings around high contrast edges to except the illumination, but the computation is too expensive. So, it is difficult to apply the conventional Retinex algorithms for time-sequential processing such as real-time video. This paper proposes a serial Retinex algorithm for time-sequential processing. With progress of processing time, the appearance will be gradually improved and the processing region will be gradually spread out. So, the proposed algorithm can obtain an MSR-like result with progress of time while limiting a processing region depending on performance of hardware.

In the following sections, at first, we review the recent progress in Retinex model. Next we propose a serial Retinex algorithm. Then we apply to some examples and verify the algorithm. Finally we make a conclusion and insight into our future work.

Retinex Model

Retinex algorithm proposed by Land[1]-[5] is based on their Mondorian experiments and improved by McCann etc.[6]. It is a classical vision model with forty years history and recently has been paid attention to again. Land suggested that color appearance is controlled by surface reflectance rather than by the distribution of reflected light and proposed three color mechanisms with the spectral responsibilities of the cone photoreceptors. He called these mechanisms Retinexes because they are thought to be some combination of retinal and cortical mechanisms.

Though various enhancements to the Retinex theory have been proposed, its key feature is that the Retinex algorithm explicitly treats the spatial distribution of illumination. According to the Path-based model based on Mondrian experiments of Land & McCann[2], the luminance difference of the separated two points in the scene is obtained by the ratio of neighboring points along the path. When the gray step patches with linear reflectance are lit by the illumination which has the opposite gradient, the sequence of darkness appearance is not changed regardless of whether each patch reflects the same light bundle physically, if the relative luminance ratios on the boundaries of each edge are traced. To estimate the distribution of illumination *L* defined in the previous section, various ways in taking paths have been published. The Random Walk model[12] computes the luminance product of each point from the distributed initial points in image by random walk. The Poisson model[13] takes the spatial gradient in illumination as the little change of second differential signal and computes it by inverse conversion. McCann-Sobel model[14] iteratively computes the luminance ratio along spiral paths while keeping on down sampling the image. Another iterative model by Funt[15] traces 8 neighbors. Iterative model is a two-dimension extension of path-based model, where the new value is calculated for each pixel by iterative comparison.

The Center/Surround (C/S) model simply estimates the luminance *L* around a pixel in consideration by averaging the image *I* with Gaussian filter. Basing on the work by Land[5], NASA[16]-[20] developed the MSR model by integrating multiple SSRs with different scales and weights. Furthermore, QP (Quadratic Programming) method minimizes a second differential cost function by determining Euler-Lagrange undefined coefficients under the constraint on spatial smoothing condition to image and illumination. Because the path-based model is complicated, concise Center/Surround model is selected by this paper. The reflectance image $R(x, y)$ is calculated by the ratio of Center $I(x, y)$ to the Surround $S(x, y)$, simply noted as $R = C/S$. The spatial distribution of illumination $L(x, y)$ is equivalent to Surround, which is calculated by averaging the original image $I(x, y)$ with a Gaussian filter.

The most representative C/S MSR model of NASA is processed in logarithmic space. The following equations describe the process.

$$R^i_{MSR}(x,y) = \sum_{m=1}^{M} w_m R^i_{SSR}(x,y,\sigma_m); i = R,G,B, \quad (1)$$

$$R^i_{SSR}(x,y,\sigma_m) = \log \frac{I_i(x,y)}{I_i(x,y) \otimes G_m(x,y)} \ ; \ i = R,G,B \quad (2)$$

$$G_m(x,y) = K_m \exp\{-(x^2+y^2)/\sigma_m{}^2\}, \quad (3)$$

$$\iint G_m(x,y)dxdy = 1 \quad (4)$$

Here, $\otimes$ means convolution.

Equation (2) expresses the SSR model with a single kernel Gaussian Surround of standard deviation c_m. The defect of the SSR is a banding artifact appears around high contrast edges. The MSR model without banding artifact has been developed by D.J.Jobson et al.[16]-[20] etc, integrating multiple SSRs with different standard deviation c_m and appropriate weight w_m.

Serial Retinex Model

Investigation of the Conventional Method

At first, we examine the conventional MSR algorithm described in the previous section for applying to time-sequential processing.

In Ref.[21], we pointed out the following problems of the MSR method in actual application.

(a) Logarithmic conversion has to be paid attention to the dark noise level in shadow and needs to limit the dynamic range expansion in the processed image.

(b) Since the basic logarithmic model treats R, G, and B channel independently and the dynamic range of each channel is normalized to the range of display device, the color balance can not be maintained so that the wide area in the image.

(c) The optimization process of c_m and w_m is unclear and decided by try and error.

In order to solve the problems, Kotera et al. proposed an adaptive scale-gain MSR model with stability stable and excellent color reproduction in linear space without using logarithmic conversion[21]. In this model, the surround image generated only from luminance image *Y*(*x*, *y*) is commonly used for R, G, and B channel, which keeps the color balance well. They also proposed an automatic setting method for weights $A(c_m)$ adapted to the scale-gain as follows:

$$R_i(x,y,\sigma_m) = \frac{C}{M}\sum_{m=1}^{M} A(\sigma_m)\left\{\frac{I_i(x,y)}{S_m(x,y,\sigma_m)}\right\}; \ i = R,G,B \quad (5)$$

$$S_m(x,y,\sigma_m) = \langle G_m(x,y) \otimes Y(x,y)\rangle; \ \sigma_m = 2^m \quad (6)$$

$$A(\sigma_m) = M\left\{\Sigma_{C/S}(\sigma_m) / \sum_{m=1}^{M}\Sigma_{C/S}(\sigma_m)\right\} \quad (7)$$

$$\Sigma_{C/S}(\sigma_m) = \left\{\frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y}\left[Y_{C/S}(x,y,\sigma_m) - Ave\{Y_{C/S}(x,y,\sigma_m)\}\right]^2\right\}^{1/2} \quad (8)$$

$$Y_{C/S}(x,y,c_m) = Y(x,y)/S_m(x,y,c_m) \quad (9)$$

However, since the computation for weights $A(c_m)$ needs the histograms of luminance SSRs corresponding to the multiple scales and takes too much time with increasing of Gaussian kernel size, it still needs improvement for practical use. So, it is difficult to the conventional algorithm to time-sequential processing.

Serial Retinex Algorithm

In this section, we develop a serial Retinex algorithm based on Ref.[21], but improve the complex calculation in Ref.[21] with keeping output quality.

Let Ω represents a set of pixels in an input image. Let $C(t) \subset \Omega$ be a subset of Ω at time $t = 1,2,\cdots$. Here, $C(0) = \phi$. For pixel (x,y) at time t with scale $m_p \in N^+$; $p = 1,2,\cdots P$, the enhanced image $R_i(x,y;t,p)$; $i = R,G,B$ can be defined as follows:

$$R_i(x,y;t,p) = \begin{cases} R_i(x,y;t-1,P) & , \quad (x,y) \in C(t-1) \\ A\dfrac{I_i(x,y)}{S_{sum}(x,y;p)} & , \quad (x,y) \in C(t) - C(t-1), \\ I_i(x,y) & , \quad otherwise \end{cases} \quad (10)$$

$$S_{sum}(x,y;p) = \frac{1}{p}S(x,y;p) + \frac{p-1}{p}S_{sum}(x,y;p-1), \quad (11)$$

$$S(x,y;p) = \langle G(x,y;m_p) \otimes Y(x,y)\rangle, \quad (12)$$

$$G(x,y;m_p) = K(m_p)\exp\left\{-(x^2+y^2)/\sigma_{m_p}{}^2\right\} \quad (13)$$

$$\iint G(x,y;m_p) = 1, \qquad \sigma_{m_p} = 2^{m_p}. \quad (14)$$

The major difference from conventional Retinex model is that the proposed model creates an integrated multi-scale luminance surround from multiple luminance surround images by Gaussian filter with different standard deviation c_{m_p}. In the proposed method, *P* times of division is avoided in the computation of multiple SSRs and replaced with the easy summation instead. Moreover, the proposed model can suppress undesired banding artifact as well as adaptive MSR model. Figure 1 illustrates the proposed model. Instead of the weighting sum of multiple SSRs, the proposed model integrates m=1~*P* different luminance surround *S* into a single surround image S_{sum}. As shown in Eq.(11), in the proposed algorithm, the weight for integration is equal in all surround. Therefore, complicated parameter setting is unnecessary.

In the proposed algorithm, two variables *p* and *t* are newly introduced for serial processing. By increasing the variable *p* and *t*, the appearance will be gradually improved by Eq.(11) and the processing region will be gradually spread out by Eq.(10), respectively. In this algorithm, the kernel size of Gaussian filter for *p*-th scale m_p is set to $\sigma_{m_p} = 2^{m_p}$, and the algorithm integrates *p* different luminance surround *S* into a single surround image S_{sum}, recursively. So, there is no need to produce multiple SSRs and computation time can be reduced in comparison with MSR techniques. Figure 2 illustrates the serial processing structure by two variables *p* and *t*.

The proposed algorithm has only one parameter *A* for scale-gain. In our experiments, an appropriate result is obtained in many cases by fixing the parameter *A* to 1.

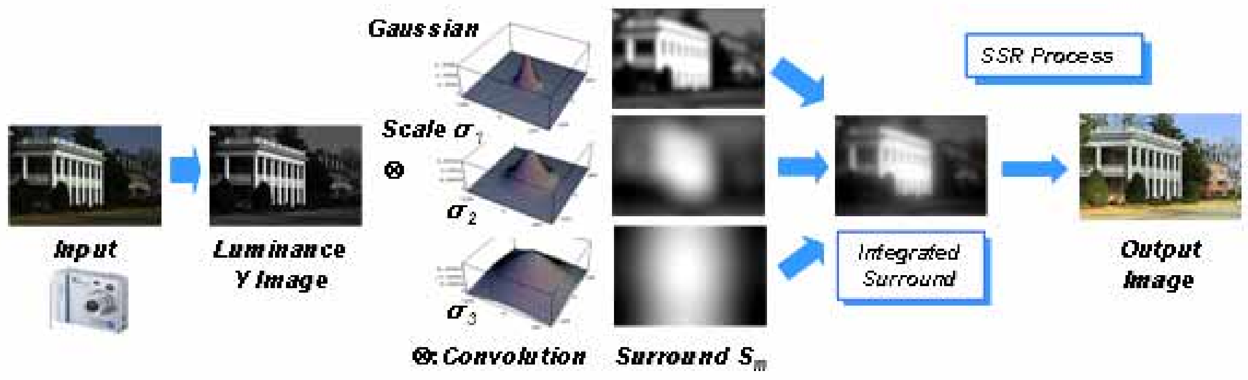


Figure 1. *Retinex model by integrating surrounds.*

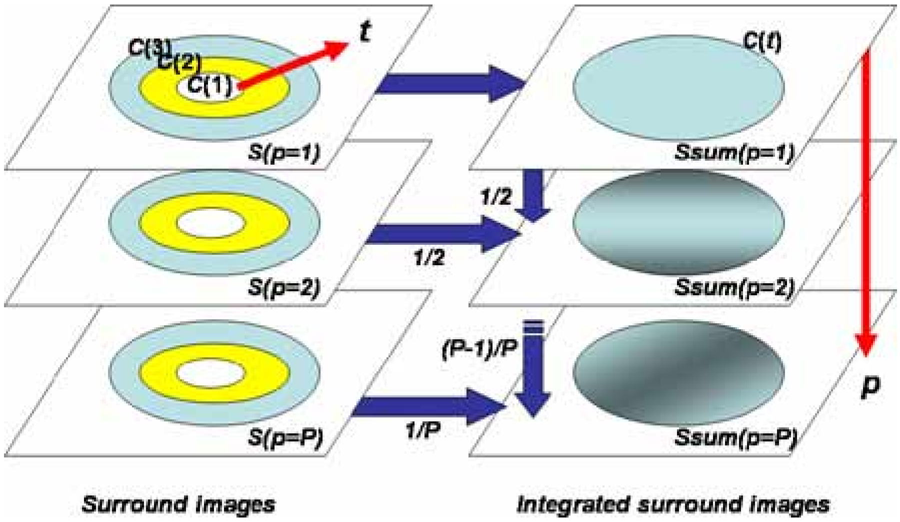


Figure 2. *Serial Retinex structure of the proposed method.*

Experiments

We show an example of application using the proposed algorithm. We developed a system for enhancing an image consecutively. In this application, $C(t)$ is set as a region within a circle with radius of t and the center is indicated by a user. This setting can simulate image enhancement around gaze point.

Experiment on still images

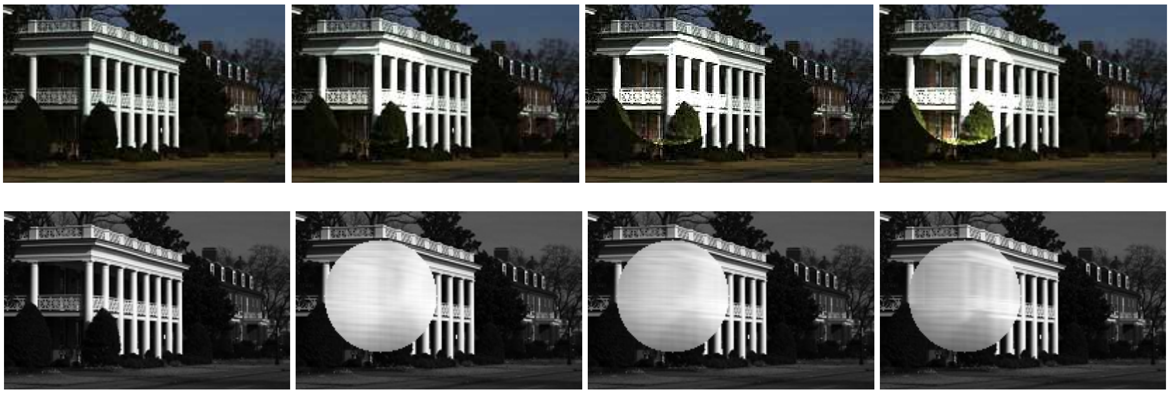
Figure 3 shows time-sequential images with increasing p. In this example, another variable t was set as constant. For example, as a value of the variable t, we should use a region of a visual angle (for example, 10 degrees). Upper images are results by the proposed Retinex and lower images are surround images S_{sum}. Figure 3(a) shows original color image and the luminance image. In the case of Fig.3(b), only one Gaussian filter with kernel size $m_1 = 7$ was used at $p = 1$ and this is the same result by the SSR. Figures 3(c) and 3(d) show the result of p=2 ($m_1 = 7$ and $m_{21} = 5$) and the result of p=3 ($m_1 = 7$, $m_{21} = 5$ and $m_{31} = 2$), respectively. As increasing the variable p, the appearance was improved by accumulating p different luminance surrounds. If the purpose of Retinex processing is limited region processing, the calculation with big size kernel must be uselessness under considering with visual characteristics. In that case, we can reduce calculation time more.

Figure 4 shows time-sequential images with increasing t. In this experiment, we used the same three kernel filters as Fig.3. As increasing the variable t, the processing region was gradually spread out.

In the proposed method, we can obtain an effect as shown in Fig.5 by moving the center of processing region. A dotted line in Fig.5 shows the trace of the center. The proposed method can process only the region that wants to perform Retinex fast.

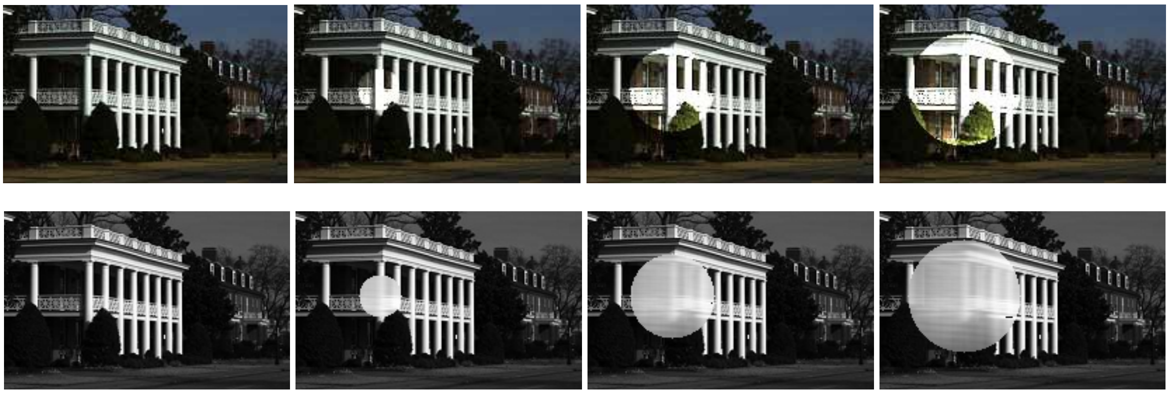
Experiment on motion pictures

There is possibility of various kinds of application in the proposed serial algorithm for moving images as well as still images. The proposed method can apply to motion pictures basically by performing still image processing for each frame. However, in the case of motion pictures, a processing region depends on performance of hardware. Furthermore, in the same way as a still image, calculation speed depends on kernel size and the number of kernel.



(a) original image (b) m_1=7 (b) m_2=5 (c) m_3=2

Figure 3. *Result of appearance improvement by increasing p. (t=30)* (Upper: output image. Lower: surround image.)



(a) original image (b) t=10 (b) t=20 (c) t=30

Figure 4. *Spatial-sequential processing by increasing t. (P=3)* (Upper: output image. Lower: surround image.)

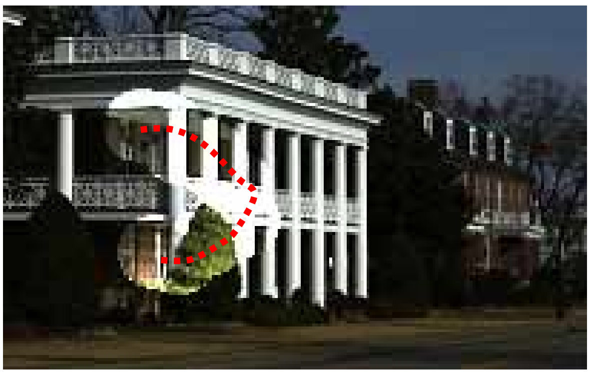


Figure 5. An example of Retinex results along a trace.

Conclusions

This paper proposes a serial Retinex algorithm for time-sequential processing. We propose an integrating surround algorithm for reducing calculation time. The quality of the output result is almost the same as conventional MSR output which can suppress the banding around high contrast edges. The proposed algorithm has two variables on time domain for sequential processing. One expresses the processing region and another expresses the kernel integration. The performance of the proposed method was verified by experiments.

The proposed algoroithm can apply to various applications for still images by appointing a processing region dynamically. However, various problems are left to apply the proposed algorithm to motion pictures. In order to handle a wide region, improvement of hardware is necessary, but there is more possibility of improvement in algorithm. Since the proposed algorithm requires processing time for convolution of big size kernel, the algorithm must be improved for real-time video processing with any size. Furthermore, it is necessary to examine appropriate processing of edge parts for practical use.

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